Response (Referee #1 comment)

Ms. Ref. No.: hess-2022-379

Title: Improving predictions of land-atmosphere interactions based on a hybrid data assimilation and machine learning method

This study proposed a hybrid data assimilation and machine learning framework to integrate in-situ and remotely sensed-based soil moisture observations and remotely sensed leaf area index (LAI) into the Weather Research and Forecasting (WRF) model. The ensemble Kalman filter (EnKF) approach is used to update the leaf biomass and specific leaf area by assimilating the remotely sensed LAI. A machine learning surrogate model is used to integrate soil moisture profile observations and remote sensing soil moisture product to estimate the three-layer soil moisture. In general, the hybrid framework coupled with the WRF model can improve the simulation of air temperature, specific humidity, wind speed, and precipitation, etc. in the Heihe River basin (HRB). In addition, the hybrid model can highlight the oasis-desert effect and improve the simulation of regional wind speed and precipitation. These results contribute to understanding regional climate and land-atmosphere interactions in the HRB with an advanced WRF model. The entire manuscript meets the scope of this journal. However, several points in the manuscript need to be addressed. So I suggest a minor revision is needed before publication.
We gratefully thank the reviewers for their review, which we believe has led to significant improvement on the original manuscript. The original reviewers' comments are reproduced below in black text and the corresponding response is shown in blue text.

Major comments:
1. The authors need to emphasize the advantages of the hybrid framework coupled with the WRF model compared to the previous Noah-MP model. This includes the innovative aspects of the study objectives, content, and results.
Thank you for your good comment. This study highlights the coupling of a hybrid data assimilation and machine learning approach with the WRF model and evaluates its performance in regional climate simulations. Compared with the direct assimilation of coarse-resolution remotely sensed soil moisture, this method can improve the estimation of soil moisture and ET in the heterogeneous land surface by utilizing soil moisture profile observations. Therefore, it is necessary to incorporate this hybrid approach in regional climate models to implement detailed land characterization information in basins with complex underlying surfaces and improve climate modeling.

The objective of this study is revised as: "Previous studies have also demonstrated the importance of the hybrid DA and ML method when estimating LAI, SM, and ET in typical arid/semi-arid regions of HRB. However, the advantages of improving the representation of soil and vegetation processes in affecting regional climate via the coupled DA and ML framework have not been fully exploited, especially in basins with complex underlying surfaces. Therefore, this study aims to investigate the improvement of the hybrid DA and ML framework for regional climate and land-atmosphere interactions in the HRB based on the WRF model and to further reveal its physical mechanisms."

2. Although the advantages of hybrid modeling are obvious, the authors still need to explain why ML methods were constructed to estimate soil moisture instead of directly assimilating SMAP soil moisture. In addition, the uncertainties in the estimation of soil moisture from the hybrid model need to be discussed.

Thanks for your comment. The advantages regarding the hybrid model will be added to section 3.2: "Compared with the direct assimilation of coarse-resolution remotely sensed SM, this method can improve the estimation of SM and ET on the heterogeneous land surface. This is because *in situ* SM profile observations are used to construct an ML-based surrogate model to improve SM and ET estimation on complex underlying surfaces."

The uncertainties in the estimation of soil moisture from the hybrid model will be added to section 4.1: "The results also indicate that the SM simulations from the WRF (DA-ML) model are hard to capture the observed peak values. This is because the prediction accuracy of ML methods is limited by the training data set. If the model is applied under extremely wet conditions with sparse training data, the performance of the hybrid model will decrease as the number of training samples decreases."

Minor comments:

1. How to match the spatial resolution of different datasets to the WRF system, for example, land cover data with a spatial resolution of 30 m, while WRF is set to 3 km.

Thanks for your comment. The land cover, soil texture, elevation, and GLASS LAI dataset were resampled to 3 km to be consistent with the model simulation resolution. The relevant sentences will be revised in the section 3.1.

2. The MODIS LAI is the most widely used remote sensing product. Describe why GLASS LAI can be used for assimilation instead of using other products.

Thanks for your comment. The GLASS LAI was generated using the general recurrent neural network (GRNN) approach based on Moderate Resolution Imaging Spectrometer (MODIS) and CYCLOPES LAI products. A series of validation studies have been implemented to evaluate various remotely sensed LAI products (Ma et al., 2017; Xu et al., 2018). The validation results of the global LAI products show that GLASS LAI exhibits a higher percentage of high-quality data and less uncertainty compared to other remote sensing products.

The following paragraph will be added to section 2: "The GLASS product has been demonstrated to have better accuracy than Moderate Resolution Imaging Spectroradiometer (MODIS) and Advanced Very High Resolution Radiometer (AVHRR) and provides time-space continuous LAI estimation (Xiao et al., 2014)."

3. The values of WRF (DA-ML) simulated LAI, 1.12, 1.05, 1.49, and 0.33, are obviously lower than the values drawn in Figure 2, especially at cropland. Another question is that the LAI of WRF (DA-ML) in Figure 2 is a little larger than the LAI of GLASS, not lower.

Thanks for your comment. To avoid ambiguity, the sentence is revised in section 4.1: "The simulated LAIs from WRF (OL) in the cropland, grassland, forest, and shrubland areas were 1.12, 1.05, 1.49, and 0.33 $m^2\ m^{-2}$, respectively, all of which were lower than that of the GLASS LAI. After assimilation, the simulated bias of the LAI from WRF (DA-ML) in the HRB can be reduced from 0.94 to 0.11 $m^2\ m^{-2}$."

4. If the horizontal coordinate in Figure 3 is Julian Day Number, its starting value should be clearly marked. Furthermore, after 200 days in the midstream, the simulation of soil moisture from the WRF (DA-ML) is hard to capture the observed peak values.

Thanks for your comment. The start horizontal coordinate values are added in Figure 3. The following sentence will be added to our manuscript: "The results also indicate that the SM simulations from the WRF (DA-ML) model are hard to capture the observed peak values. This is because the prediction accuracy of ML methods is limited by the training data set. If the model is applied under extremely wet conditions with sparse training data, the performance of the hybrid model will decrease as the number of training samples decreases."

5. Line 252: The reliability of ETMap should be described.

The following paragraph will be added to section 2: "The retrieved ET from the ETMap agrees well with the LAS observations. The multi-site averaged R^2, root mean square error (RMSE), and mean absolute percentage error (MAPE) values are 0.68, 0.85 mm day^{-1}, and 20.27%, respectively. These results confirm that the ETMap can effectively validate watershed ET simulations."

6. Line 265: In the validation work, air temperature and specific humidity simulations and observed heights need to be listed.

Thank you for your comment. The sentence is revised in section 4.3: "The monthly averaged 2 m air temperature and specific humidity from the WRF (OL), WRF (DA-ML), and corresponding observations at nine sites are shown in Figure 8 and 9."

7. Figure 6 and 7: The standard deviation of the observations is missing at Hulugou station.

Thank you for your comment. The standard deviations of the observations at Hulugou station are added to Figures 8 and 9.

8. Figures 9 and 10 show the Mean vertical profile of differences in air temperature and specific humidity between the WRF (DA-ML) and WRF (OL) during the growing season in 2015 in the midstream and downstream oasis. However, the vertical profile locations are unclear even though the rectangle has been marked in Figure 8. And I want to confirm the mean vertical profile of Figures 9 and 10 should be marked as a line or a rectangle area.

Thank you for your comment. The vertical profile simulations are averaged from the rectangular area.

9. Line 403: "The height is about 650hPa". Can hPa be converted to m?

Revised.

10. Line 417: "Driven by background northerly winds, more water vapor fluxes from the midstream oasis region were carried to the upstream region". This conclusion is hardly obtained from the Figure 13.

Thanks for your comment. The meridional circulation of the mid- and downstream oasis is added to the appendix. According to Figure A1, the airflow over the midstream oasis is mainly controlled by the background northerly wind. Therefore, the water vapor produced in the midstream oasis is carried to the upstream mountains and generates precipitation.

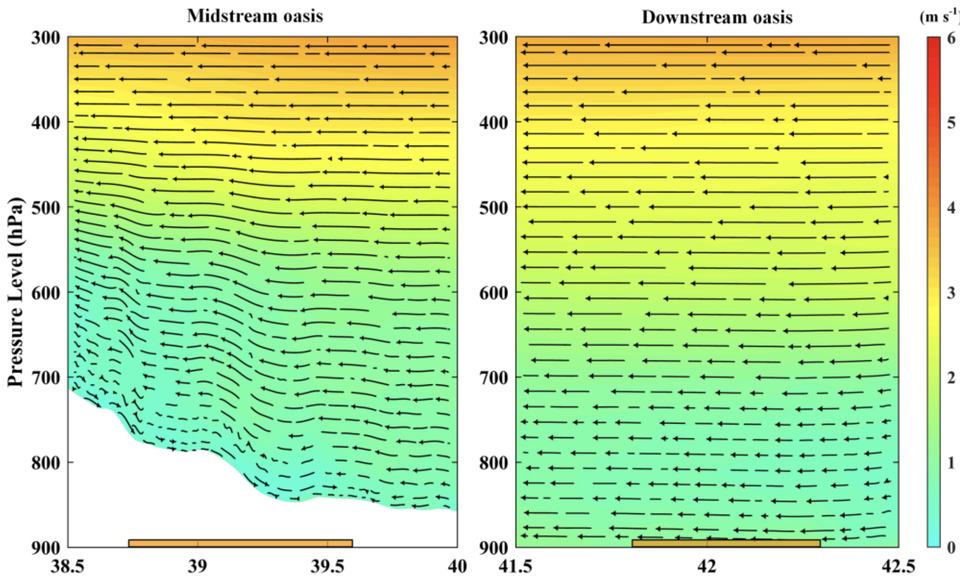

Figure A1. The zonal mean vertical velocity and meridional circulation from the WRF (DA-ML) model in the mid- and downstream oasis. The orange bar represents the oasis area.

We rephrased the sentence as "Driven by background northerly winds (Figure A1), more water vapor fluxes from the midstream oasis region were carried to the upstream region."

11. The size of the horizontal and vertical coordinates in Figure 13b and c are too small.

Thanks for your comment. The coordinates in Figure 13b and c are enlarged in the manuscript.

References:

Ma, H., Liu, Q., Liang, S., Xiao, Z., 2017. Simultaneous Estimation of Leaf Area Index, Fraction of Absorbed Photosynthetically Active Radiation, and Surface Albedo From Multiple-Satellite Data. IEEE Trans. Geosci. Remote Sens. 55, 4334–4354. https://doi.org/10.1109/TGRS.2017.2691542.

Xiao, Z., Liang, S., Wang, J., Chen, P., Yin, X., Zhang, L., Song, J., 2014. Use of general regression neural networks for generating the GLASS leaf area index product from time-series MODIS surface reflectance. IEEE Trans. Geosci. Remote Sens. 52(1), 209–223. https://doi.org/10.1109/TGRS.2013.2237780.

Xu, B., Li, J., Park, T., Liu, Q., Zeng, Y., Yin, G., Zhao, J., Fan, W., Yang, L., Knyazikhin, Y., Myneni, R.B., 2018. An integrated method for validating long-term leaf area index products using global networks of site-based measurements. Remote Sens. Environ. 209, 134–151. https://doi.org/10.1016/j.rse.2018.02.049.